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Impact of motivation and technology factors to predict satisfaction and continued intentions toward online courses

Qing Wang[(a)], Muhammad Saqib Khan[(b)*]

[(a)] *Lecturer, School of Economics and Management, Huazhong Agricultural University, Wuhan 430072, China*
[(a)] *Scholar School of Management, Huazhong University of Science and Technology 1037, Luoyu Road, Wuhan, 430074, P.R.China*

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ABSTRACT

The rapid developments and diffusion of new technologies abruptly changed world dynamics. This study pursued the motivational factors (controlled and autonomous) and technology factors (perceived ease of use and perceived usefulness) to predict the students perceived satisfaction and continued intention toward MOOCs. Using an online survey, this research collected data from 333 students, and analysis performed through PLS-SEM. The findings revealed that controlled motivation positively influenced the perceived satisfaction. However, autonomous motivation positively affected students perceived satisfaction and continued intention toward MOOCs. The technology factors such as PEU strongly impacted PU. Similarly, PU positively impacted students perceived satisfaction and continued intention toward MOOCs. This research guides essential theoretical insights and provides practical guidelines to educational institutions and technologists to develop and implement systems and strategies in online environments.

Introduction

The rapid developments and diffusion of ICTs (information and communication technologies) meaningfully alter today's environment, as ICTs provide new and diverse approaches for effectively delivering education (Lee, 2010). Similarly, recent developments in the world wide web (WWW) and other digital technologies, including mobile or live stream technologies, have revolutionized the world (Atique et al., 2021; Chen & Chen, 2018), and the educational sector has also been reformed by following this digital revolution. Thus, access to new learning resources has increased dramatically in recent years, and new technologies supported educational opportunities in different ways. Consequently, the higher education sector (HES) introduced online learning platforms and offered many online courses to influence students while reducing costs (Daniel et al., 2015). In recent years, competition between private and public higher education institutions has increased at the worldwide level. Therefore, many universities are taking new measures to develop strategies to attract students worldwide with an innovative and quality education that creates value. Thus, the new innovative digital system reflects a favorable impact on society (Atique et al., 2021). Since online learning's rapid growth observed to develop theory and practice, in the same way, students' perceptions, behaviors, and motivations have been studied in different online environments (Gupta Kriti, 2019).

The modern development in distance learning by introducing Massive Open Online Courses (MOOCs) can be observed as a big transformation in the education sector (Wang et al., 2021; Zhou, 2016). According to I. Pozón et al. (2019), MOOCs help students through different online learning worldwide to achieve their objectives. Thus, it is important for researchers to extensively research this topic in the education sector and mainly in the higher education sector. MOOCs are the most innovative and advanced online learning approach considered a revolutionary change in open online educational resources (Al-Adwan, 2020). Gameel and Wilkins (2019) defined that "MOOCs are online learning courses that enable students to register and participate in an online education process that might consist of thousands of other students." As large numbers of students enrolled, MOOC learning platforms enhance

* *Corresponding author. ORCID ID: 0000-0002-7722-1018*

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education quality worldwide, and many online courses are available in different disciplines. Thus, MOOCs are increasingly famous for their easy adaptability, transparency, and self-organization during the past few years.

Prior research found that students high drop-out from using MOOCs gained researchers attention to investigate MOOCs as a disruptive technology that can be viewed from two perspectives: first to consider benefits of better access to society and education, and second, it is a new learning platform and marketing opportunity (Conole, 2016). Similarly, previous research mainly focused on developing a better understanding by following various goals and motivations underlying the experience of MOOC students (Alraimi et al., 2015; de Barba et al., 2016; Zhou, 2016). Thus, these research studies highlighted motivation being a psychological concept, indicating that motivation influences learners to complete or continue to use MOOCs. Other research studies found that while using MOOCs, learners' internal motivation influence them such as personal interests, a curiosity of new learning, and many external factors that influence them to participate in MOOCs such as universities reputation and job competency development (Alraimi et al., 2015; Wu & Chen, 2017). Therefore, many students use MOOCs to gratify their interest with little or no intentions to complete the entire course (Anderson, 2013). Thus, it shows that students' motivation complexity and their use of MOOCs patterns required further investigation (Joo et al., 2018).

The TAM (technology acceptance model) (Davis et al., 1989) is one of the most common frameworks used for technology adoption in various perspectives. Using the external variables, PEU and PU, the TAM predicts the learner's behavioral intention and actual use of technology (Venkatesh & Davis, 2000). The TAM is also considered the best fit model for investigation, particularly in adopting different online learning technologies from various perspectives (Bazelais et al., 2018). Although TAM is widely applied in different industries and environments but considering the TAM role in the development of MOOCs, prior research investigated the TAM to predict behavioral intentions in Taiwan, China, and Jordan (Al-Adwan, 2020; Hsu et al., 2018; Teo & Dai, 2019), and to predict emotions, satisfaction, and MOOC use intention in Spain (Irma et al., 2020). Besides, research is on the topic still in a limited scope (Joo et al., 2018). The TAM application is still lacking, particularly with controlled and autonomous motivation to predict the users' perceived satisfaction and continued intentions toward using MOOCs.

The idea of an intention to continue with adopting new technology or system was proposed by Bhattacherjee (2001), who suggested that people are continuously using it when they experience and happy with the initial uses. The continuing intent helps to broaden understanding of the students' motivation and participation toward MOOCs. For example, Huang et al. (2017) argued that many MOOC studies focused on early involvements, and few studies are available about students' intentions to continue MOOC usage. Wu and Chen (2017) also suggested that MOOC is included in two phases, first, an initial stage of perception and adoption and an advantages stage, which implies the need to examine, over and above initial acceptability, factors influencing the continual use of MOOCs by learners. Thus, this study is worthwhile for further investigating MOOCs to check the students' perceived satisfaction and continuance intentions.

In this background, designing attractive and effective online learning environments requires various factors (i.e., motivation and technology) that influence students' perceptions and learning. Therefore, this research examines the motivation and technology factors that affect the users' perceived satisfaction and continuous intentions to use MOOCs. This research follows the self-determination theory and TAM that persuade the adoption of online information systems. These theories contributed to an empirical analysis of perceived satisfaction and continued intentions toward MOOCs. Thus, it is essential to answer the following questions in order to achieve the research objectives:

To what extent motivational factors (self-determination theory) influence users' perceived satisfaction and continued intentions toward MOOCs?

How technology factors (TAM) influence the users' perceived satisfaction and continued intentions toward MOOCs?

Does perceived satisfaction influence users' continued intentions toward MOOCs?

This study is organized in the following structure. First, we introduce the topic with importance, research gaps, and research questions. Then, we explain the supportive literature, theoretical framework, and research methodology. Finally, we perform analysis, discussions of results, and research concluded with implications and provided future research guidelines.

Literature Review

This research investigates the motivational factors (self-determination theory) and technology factors (TAM) to predict the users' perceived satisfaction and intentions to use MOOCs continuously. Thus, it is essential to understand the SDT and TAM in the MOOCs context.

Theoretical and Conceptual Review

This research followed self-determination theory (Ryan & Deci, 2000) and its underlying motivational factors considered essential to influence students' participation in MOOCs. The self-determination theory (SDT) involved two motivational factors controlled and autonomous motivation. Prior research demonstrated that the motivation of learners' for MOOCs applied both autonomous and controlled factors, indicating the need to measure students' level of self-determination. When external factors inspire the person's autonomous behavior, the self-determination level decreases. On the other hand, the self-determination level is high when a person's autonomous behavior is internally motivated. The SDT plays an essential role in technology acceptance research in online learning settings (Nikou & Economides, 2017).

Davis et al. (1989) presented a technology acceptance model comprised of perceived ease of use (PEU) ("the degree to which a person believes that using a particular system would be free of physical and mental effort") and perceived usefulness (PU) ("the degree to which a person believes that using a particular system would enhance his/her job performance"). Similarly, PEU affects the PU, and simultaneously these variables effects acceptance intentions. Many researchers attempted to extend the TAM with the help of these two variables, which do not adequately reveal acceptance (Venkatesh et al., 2003; Venkatesh et al., 2012). However, TAM is still a simple and most accepted model commonly used when evaluating individuals' intentions toward technological perspectives (King & He, 2006).

Empirical Review and Hypotheses Development

Recent research has sought to uncover the diversity and complexity of students' motivation to participate in MOOCs. This phenomenon is discussed by Clow (2013), who explains that MOOC students went through a process of four steps as "awareness, registration, activity, and progress" toward the use of MOOC. Clow concluded that very few learners achieve the fourth stage. Several qualitative research studies have guided through valuable understandings into various motivation and student participation patterns (Littlejohn et al., 2016; Zheng et al., 2015). On the other hand, empirical studies revealed that how motivation works in MOOC perspectives is still in a limited scope and at the initial stage (de Barba et al., 2016). For example, Zhou (2016) used self-determination theory and concluded that students' autonomous motivation positively affected their attitude toward MOOCs, stressing their less autonomous position in open learning settings such as MOOCs. Joo et al. (2018) used SDT and found that self-determination did not affect Korean students' satisfaction toward K-MOOC. Thus, prior research also revealed inconsistent findings that requires more research to generalize the results.

Previous research endeavored to incorporate the TAM and SDT to observe learners' intention toward mobile assessment systems and found that PEU positively affected PU (Nikou & Economides, 2017). Wu and Chen (2017) found that PEU significantly impacted PU in the MOOC usage context. Similarly, the TAM factors significantly impacted user satisfaction that enhanced continuance intentions in Korea (Joo et al., 2018). Hsu et al. (2018) found that external factors such as perceived convenience, sense of community, computer self-efficacy, and perceived gains positively impacted PEU and PU significantly affected user attitude and behavioral intentions in Taiwan. Teo and Dai (2019) found that the TAM factors explained 45% variance toward MOOCs in China. However, the time factor was not associated with attitude and intention, but it was an important predictor of PU. Recently, Al-Adwan (2020) found that the TAM factors effectively impacted user attitude and behavioral intentions toward MOOCs in Jordan. Likewise, the TAM factor such as PU was significantly impacted satisfaction that enhanced the user intentions toward MOOCs in Spain. Besides all the above discussion, still, this topic discussed in a limited scope and required more research (Joo et al., 2018). This research employed the SDT and TAM factors (PEU and PU) to determine the students' perceived satisfaction and continued intentions toward MOOCs.

Theoretical Model Development

This study follows the self-determination theory and TAM to predict the users perceived satisfaction and continued intentions to use the MOOCs. Figure 1 depicts the theoretical model of the proposed research.

Autonomy is the central concept of self-determination theory, described as "the perceived origin or source of one's own behavior. Autonomy concerns acting from interest and integrated values. When autonomous, individuals experience their behavior as an expression of the self …" (Ryan & Deci, 2000, p. 8). Control is opposed to autonomy. Individual behavior can be stimulated through internal induced incentives (called "autonomous motivations"), as well as through external evoked incentives (called "controlled motivations") (Zhou, 2016).

Controlled Motivation

The word motivation comes from the concept of movement that refers to an individual's instincts and impulses that influence to act accordingly. Researchers established a distinction between extrinsic and intrinsic motivation as essential factors (Magen-Nagar & Cohen, 2017). Controlled motivation is contrary to autonomous motivation. Thus, controlled motivation acts as an obstacle to develop positive perceptions, though the effects can differ between self-perceptions and technology (Zhou, 2016). Prior research found that controlled motivation negatively affects behavioral intentions. For example, Ryan and Deci (2000) discussed that controlled motivation might cause negative outcomes for individuals due to internal and external pressures. Similarly, recent research revealed that controlled motivation had non-significant impacts on user intentions toward MOOCs (I. Pozón et al., 2019; Irma et al., 2020) and continues intentions toward MOOCs (Abdullatif & Velázquez-Iturbide, 2020). Self-determination theory explains that higher motivation does not mean to yield positive outcomes, mainly if the motivation is controlled than autonomous (Ryan & Deci, 2000). Similarly, prior research revealed that controlled motivation negatively impacts satisfaction, such as in the context of employee satisfaction and turnover (Gillet et al., 2013) and child and parent association context (Jungert et al., 2015). Thus, we assume the following hypothesis:

H_1: Controlled motivation negatively impacts users continued intentions toward MOOCs.

H_2: Controlled motivation negatively impacts users perceived satisfaction toward MOOCs.

Autonomous Motivation

Autonomous motivation is more important than controlled motivation—autonomous motivation is considered an inner reward that motivates individual behavior (Zhou, 2016). Prior research found that autonomous motivation positively related to students' use intentions toward MOOCs (I. Pozón et al., 2019; Irma et al., 2020) and continuous intentions toward MOOCs (Abdullatif & Velázquez-Iturbide, 2020). Similarly, previous research found the positive relationships of autonomous motivation and satisfaction, such as in the context of employee satisfaction and turnover (Gillet et al., 2013), child and parent association context (Jungert et al., 2015). Thus, we develop the following hypotheses:

H_3: Autonomous motivation positively impacts users continued intentions toward MOOCs.

H_4: Autonomous motivation positively impacts users perceived satisfaction toward MOOCs.

Perceived Ease of Use

Perceived ease of use (PEU) is commonly used in literature by considering different empirical research studies from various perspectives. Empirical evidence revealed that PEU had significant relationships on user intentions (directly/ indirectly) and its positive effect on PU (Venkatesh & Davis, 2000). When students believe the e-learning system is likely to be easy to use, they will accept and use the system more positively and continuously (Lee et al., 2009). Cigdem and Ozturk (2016) discussed that the direct effects of PEU on perceived usefulness could inspire to reflect that system is functioning well and beneficial for the users. Huanhuan and Xu (2015) revealed that PEU positively affected and interacted with user intentions toward MOOCs. Thus, in view of these two factors, the authors assessed the ease of the platform, i.e., whether the user was prepared to participate and finish the online course as well as whether interactive learning was important to them. Similarly, past research demonstrated that PEU positively impacted perceived usefulness and users' continuance intentions toward online learning technologies (del Barrio-García et al., 2015; Lee, 2010; Xu, 2015). Therefore, we assume the following hypotheses:

H_5: Perceived ease of use positively impacts users continued intentions toward MOOCs.

H_6: Perceived ease of use positively impacts users perceived usefulness toward MOOCs.

Perceived Usefulness

According to Sun et al. (2008), the perceived usefulness and easy use of online courses offer and file transfer system positively impacted students' attitude toward online learning. Further, they found that perceived usefulness was positively enhanced learning and adoption of e-learning systems. Some other empirical research studies found that perceived usefulness positively impacted students' behavioral intentions toward online learning through MOOCs (Al-Adwan, 2020; Tawafak et al., 2020; Teo & Dai, 2019) and continuance intentions toward e-learning use (Saeed Al-Maroof et al., 2021). Similarly, several past research studies provided empirical backup for the significance of perceived usefulness on satisfaction in e-learning contexts (Cigdem & Ozturk, 2016; Lee, 2010; Thong et al., 2006) and toward MOOCs (I. Pozón et al., 2019; Irma et al., 2020). del Barrio-García et al. (2015) found that the system's perceived usefulness positively influenced the students' satisfaction, especially among students who had a high need of cognition. Thus, we define the following hypotheses:

H_7: Perceived usefulness positively impacts users continued intentions toward MOOCs.

H_8: Perceived usefulness positively impacts users perceived satisfaction toward MOOCs.

Perceived Satisfaction

Perceived satisfaction is used to evaluate a system's success or failure (Cigdem & Ozturk, 2016), especially user satisfaction positively affected to use the e-learning system continuously (Mohammadi, 2015). Therefore, many research studies confirm empirical support to the direct effect of satisfaction on the users' use intention of technology in MOOCs contexts (I. Pozón et al., 2019; Irma et al., 2020). Some other research studies also found that perceived satisfaction significantly impacted the user continuance intentions toward MOOCs' use (Alraimi et al., 2015; Joo et al., 2018; Shahijan et al., 2016). So, we purpose following hypothesis:

H_9: Perceived satisfaction positively impacts users continued intentions toward MOOCs.

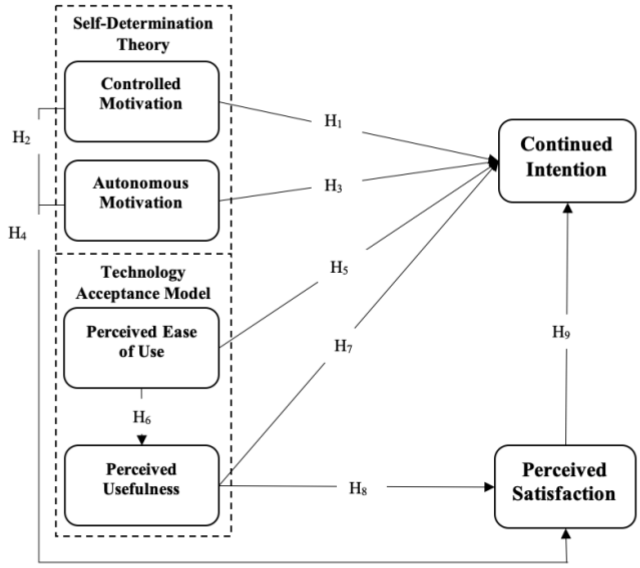

Figure 1: Theoretical Research Model

Research and Methodology

Instrument Design and Measurement Scale

The structured questionnaire was designed in the English language. The questionnaire was designed in two sections and prepared in MOOCs context. Before designing the questionnaire, we explained the research motives and research ethics about user information privacy. The first section consisted of research 26 questions asked from intended users to accomplish the research objectives. The second section was based on users' demographic information. We used the established scales of prior research, such as controlled motivation (CM) with 4 items and autonomous motivation (AM) with 5 items were adapted from Zhou (2016) and Irma et al. (2020). Similarly, perceived ease of use (PEU) with 4 items and perceived satisfaction with 7 items were adapted from Sun et al. (2008). Perceived usefulness (PU) with 3 items taken from Alraimi et al. (2015). The continued intention with 3 items was adapted from Chiu and Wang (2008). All items were measured based on a seven-point ("1=strongly disagree and 7=strongly agree") Likert scale. After preparation, this questionnaire was discussed with five Ph.D. students and two associate professors. After incorporating their feedback, we finalized the questionnaire for data collection.

Data Collection and Sampling

We posted the final questionnaire on a leading online survey website in China (https://www.wjx.cn). The online survey was launched in three public universities in Wuhan, China, and asked the intended students to fill the questionnaire. We used convenience sampling, commonly used in massive open online courses research (Al-Adwan, 2020; Wang et al., 2021). Further, convenience sampling is a useful technique commonly used for data collection from intended respondents in a timely and efficient manner (Safeer et al., 2020; Sekaran & Bougie, 2016). Finally, we collected data from 333 students who were currently participating in different online courses in the MOOCs context. After thoroughly data screening, removing biased responses and outliers, we considered 305 responses for final analysis. The demographics information of respondents is revealed in the following table 1.

Table 1: Participants Demographics Information

Description	Number	%
Sample Size	**305**	
Gender		
Male	237	77.70%
Female	68	22.30%
Age		
18 – 23	51	16.72%
24 – 29	127	41.64%
30 – 34	93	30.49%

35 – 40	34	11.15%
Education		
Bachelor	67	21.97%
Master	137	44.92%
Doctoral	101	33.11%
Annual Family Income		
$3,000 - $7,000	206	67.54%
$7,001 - $11,000	48	15.74%
$11,001 - $15,000	23	7.54%
$15,001 - $19,000	19	6.23%
Above $19,000	9	2.95%

Results and Discussions

This research applied the partial least square (PLS) via structural equation modeling (SEM) through Smart PLS 3.2.8 version software (Ringle et al., 2015). PLS-SEM technique supports researchers in managing complex models and multiple relationships without data normality assumptions (Safeer et al., 2020). When the research objectives are predictions and contribute to theory, PLS-SEM is the best fit to apply according to the recommendation of Sarstedt et al. (2017) and Hair Joseph et al. (2019). PLS-SEM involves assessing the model in two parts. The first part was related to model measurement evaluation, and the second part consisted of structural model evaluation.

Measurement Model Evaluation

The measurement model is comprised of two parts. The first part is related to measures the constructs ICR (internal consistency reliabilities) by including item loadings, Cronbach's Alpha, and Composite reliability. The second part comprised the constructs' validity by including AVE (average variance extracted), discriminant validity.

Hair Joseph et al. (2019) recommended that item loading values should be higher than 0.708. However, values between 0.60 to 0.70 are also acceptable for data analysis appropriately in PLS-SEM. Similarly, several other authors recommended that Cronbach's alpha and composite reliability values must be more than 0.70 and AVE values must be greater than 0.50 for suitable analysis in PLS-SEM (Chin, 1998; Hair Jr et al., 2017; Sarstedt et al., 2017). Our all values of item loadings, Cronbach's alpha, and composite reliability fulfilled the recommended criteria (see table 2 for detailed results). However, the item loading value of PS7 was 0.694, which was less than the recommended criterion (0.708), but it was acceptable for analysis (see figure 2). Similarly, all values of AVE were also greater than 0.50, which had satisfied the criterion. Therefore, constructs ICR was established.

Table 2: Internal Consistency Reliability and Validity

Constructs	Items	Loadings	Cronbach's Alpha	CR	AVE
Controlled Motivation (CM)	CM1	0.830	0.783	0.858	0.602
	CM2	0.712			
	CM3	0.835			
	CM4	0.719			
Autonomous Motivation (AM)	AM1	0.881	0.922	0.941	0.762
	AM2	0.884			
	AM3	0.834			
	AM4	0.884			
	AM5	0.879			
Perceived Ease of Use (PEU)	PEU1	0.852	0.889	0.923	0.750
	PEU2	0.853			
	PEU3	0.865			

	PEU4	0.894			
Perceived Usefulness (PU)	PU1	0.917	0.893	0.934	0.824
	PU2	0.902			
	PU3	0.904			
Perceived Satisfaction (PS)	PS1	0.786	0.894	0.917	0.612
	PS2	0.782			
	PS3	0.810			
	PS4	0.813			
	PS5	0.795			
	PS6	0.790			
	PS7	0.694			
Continued Intention (CI)	CI1	0.879	0.858	0.914	0.779
	CI2	0.874			
	CI3	0.895			

Table 3 revealed that the discriminant validity also fulfilled the criterion recommended by Fornell and Larcker (1981), explaining that the constructs' AVE values must be greater than the other constructs' correlation values. Thus, our results have also established discriminant validity.

Table 3: Fornell-Larcker Criterion

Construct	AM	CI	CM	PEU	PS	PU
AM	0.873					
CI	0.817	0.883				
CM	0.738	0.720	0.796			
PEU	0.782	0.730	0.670	0.866		
PS	0.838	0.805	0.776	0.747	0.852	
PU	0.830	0.798	0.715	0.782	0.786	0.908

Structural Model Evaluation

Generally, structural model evaluated through applying various tests in PLS-SEM such as testing multicollinearity, testing of R^2 (coefficient of determination) for checking explained variance, model predictive power (Q^2 value), model fit, and hypotheses testing for evaluation of results (Hair Jr et al., 2017). First, we tested the data multicollinearity and found that all collinearity values were less than 5, matching the recommended criterion by Hair Joseph et al. (2019). Thus, there was no multicollinearity problem in the data. Next, we tested the R^2 to evaluate the explained variance in endogenous constructs and found that the R^2 value of perceived usefulness was 0.611 (61.1%), considered medium to strong, and the R^2 value of perceived satisfaction was 0.767 (76.7%) considered strong. The R^2 value of continued intention was 0.746 (74.6%), also considered strong (Chin, 1998). Thus, our proposed model revealed a strong explained variance in endogenous constructs. Figure 2 displayed the R^2 values of all endogenous constructs.

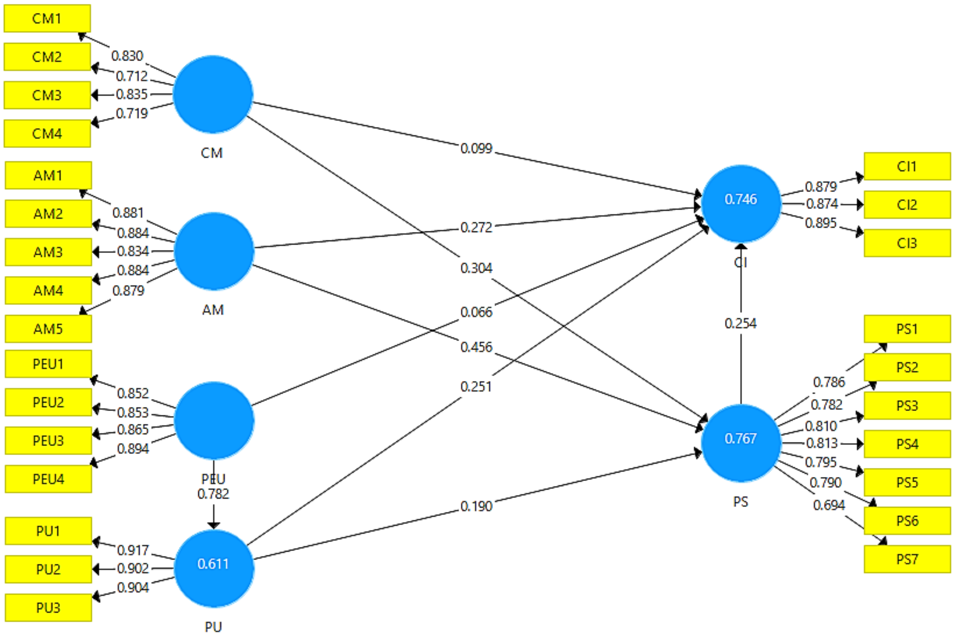

Figure 2: R^2 Values of Proposed Model

Next, we tested the Q^2 values to check the model's predictive power or accuracy. Therefore, we applied the blindfolding procedure of Geisser (1974) to test the Q^2 values of all endogenous constructs and found that the Q2 value of perceived usefulness was 0.475 and perceived satisfaction was 0.437, both values were considered medium to strong, and continued intention Q2 value was 0.543 considered strong as recommended by Hair Joseph et al. (2019). Thus, our proposed model had medium to strong predictive power or accuracy.

According to Chin (1998) and Hair Jr et al. (2017), the model fit can be evaluated by checking the RMSEA value in PLS-SEM. This study found the RMSEA value of 0.061, which was good. However, a value less than 0.08 is considered acceptable (Chin, 1998).

Hypotheses Testing and Results Discussion

Next, we tested the proposed hypotheses. The total scores and constructs' measurement errors may affect the path coefficients. Therefore, we used the bias-corrected and accelerated (Streukens et al., 2010) bootstrapping with 5000 subsamples, two tails at 0.05 significance level to check the path co-efficient, p-values, and t-values for testing hypotheses (Hair Jr et al., 2017). All results are displayed in table 4.

Table 4: Hypotheses Testing Results

Hypothesis	Constructs	Path Coefficient	t value	p-value	Support
H_1	**CM -> CI**	0.099	1.780	0.075	No
H_2	**CM -> PS**	0.304	6.021	0.000	Yes
H_3	**AM -> CI**	0.272	3.313	0.001	Yes
H_4	**AM -> PS**	0.456	8.210	0.000	Yes
H_5	**PEU -> CI**	0.066	0.978	0.328	No
H_6	**PEU -> PU**	0.782	26.869	0.000	Yes
H_7	**PU -> CI**	0.251	3.486	0.000	Yes
H_8	**PU -> PS**	0.190	3.157	0.002	Yes
H_9	**PS -> CI**	0.254	3.729	0.000	Yes

This research found that controlled motivation (CM) did not affect user continued intentions (CI) as CM -> CI (β=0.099; p=0.075). Thus, null hypothesis H_1 was accepted. The current literature lacks the relationship between CM and CI. However, similar research supported this finding that Irma et al. (2020) and I. Pozón et al. (2019) that controlled motivation did not affect user MOOC use intention in Spain. Although these relationships were not significant, differing from other reviewed studies, they found similar results compared to the previous studies. For instance, reviewing Mikalef et al. (2016), the current research could not find significant relationships between controlled motivation and user continued intention. The finding was also consistent with the self-determination theory. Thus, it explained that controlled motivation did not influence the students to use massive open online courses continuously.

H_2 found that CM significantly impacted perceived satisfaction (PS) as CM -> PS (β=0.304; p=0.000). So, null hypothesis H_2 was rejected. Although literature lacks in the current research context and no similar research found on the topic. However, these relationships found contrary results compared to previous research of Gillet et al. (2013), who found that work-controlled motivation negatively impacts work satisfaction. Similarly, Koestner et al. (2008) found that controlled motivation was not related to personal goal progress. Self-determination explains that controlled motivation consists of external factors or regulations, which has shown a kind of motivation that influences individuals to act for external rewards (Ryan & Deci, 2000). Thus, we can expect that university and MOOC regulations influence the students' satisfaction to act and follow regulations for a certificate (a kind of achievement).

H_3 – H_4 revealed that autonomous motivation (AM) positively impacted CI and PS. Therefore, H_3 – H_4 was supported. Figure 3 revealed the path coefficients and significance level of all constructs. Our findings followed the prior similar research of I. Pozón et al. (2019), who found that autonomous motivation enhances MOOC users' intention in Spain. Similarly, Zhou (2016) found that autonomous motivation positively enhances students' intention to use MOOC in China. However, there is scarce research in the context of continuous intention. Similarly, our findings also supported earlier research in perceived satisfaction perspectives. For example, Gillet et al. (2013) revealed that autonomous work motivation positively enhanced employee work satisfaction. Thus, our findings also discovered that autonomous motivation positively enhanced the students perceived satisfaction toward MOOC. Similarly, this study's findings are also in line with the self-determination theory (Ryan & Deci, 2000).

H_5 found that PEU had no effect on CI as PEU -> CI (β=0.066; p=0.328). The results are in line with earlier similar research of I. Pozón et al. (2019), who found the perceived ease of use had no effect on MOOC users' intention in Spain. However, other research of Yang et al. (2017) deviated from our results, who found that perceived ease of use positively affected continued intention toward participating in MOOCs. Thus, these inconsistent findings may require further research to generalize the findings.

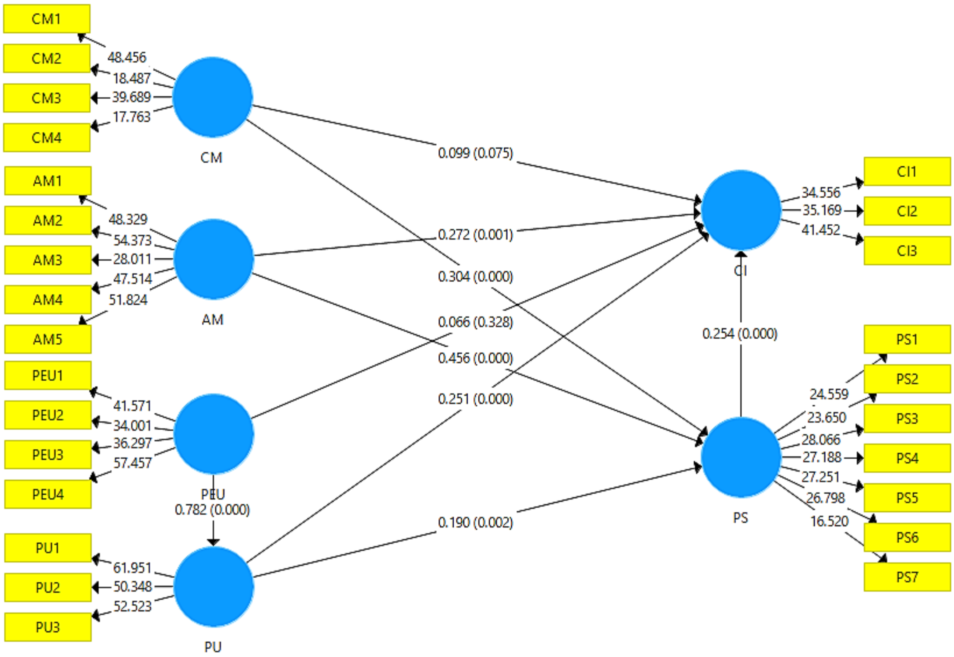

Figure 3: Path Coefficients and Significance Level

H_6 found that perceived ease of use strongly affected perceived usefulness. Thus, hypothesis H_6 was supported. Our finding is consistent with earlier similar research of Irma et al. (2020) and Yang et al. (2017), who found that perceived ease of use positively facilitated users to enhance their usefulness toward MOOCs. Thus, the TAM factors supported enhancing the students' continued intention toward MOOCs.

H_7 – H_8 revealed that perceived usefulness significantly affected continued intention and perceived satisfaction. So, H_7 – H_8 were supported. Our findings supported Yang et al. (2017) earlier work, who found that perceived usefulness enhanced the students' continued intention in massive open online courses. Similarly, Ouyang et al. (2017) found that perceived usefulness not only enhances the students' satisfaction but also positively increases the students' continued intentions to use MOOC. Thus, our study contributed and generalized the findings by following prior research.

H_9 found that perceived satisfaction positively impacted users' continued intention. Therefore, H_9 was supported. The findings explained that perceived satisfaction was a very important determinant that increased students' continued intention toward MOOCs. Our findings are consistent with previous research of Lu et al. (2019), who found that satisfaction was an essential factor of user continued intention, particularly in the MOOC perspective. Similarly, Ouyang et al. (2017) verified that satisfaction was important for users to increase their intentions continuously. Therefore, technology factors are important for students to enhance their perceived satisfaction and continue using MOOCs.

Conclusions

The investigation of behavior continuity is valuable in the information system and more essential than behavior acceptance (Ouyang et al., 2017). This research aimed to investigate the motivation and technology acceptance factors to predict the users' perceived satisfaction and continued intention toward MOOCs. The findings revealed controlled motivation is an essential factor that enhanced the users' perceived satisfaction. However, autonomous motivation significantly affected users' perceived satisfaction and continued intentions toward massive open online courses. Likewise, technology factors such as perceived ease of use enhanced the usefulness. While perceived usefulness positively enhanced the users' perceived satisfaction and continued intentions simultaneously. Therefore, technology acceptance factors perfectly influenced users toward MOOCs. Thus, educational institutions and technology experts may focus on these important motivational factors and technological factors for developing ease use and effective MOOCs online platforms to influence multiple users for enhancing their perceived satisfaction and continuance use of MOOCs.

This research develops a better understanding of students' perceived satisfaction and continued intention about MOOCs and provides important practical guidelines to educational institutions and MOOCs designers who offer multiple online courses to influence students. Considering controlled and autonomous motivation factors, they can influence the students' perceived satisfaction, mainly through following their achievements such as certificates, personal growth, and developments for their better future career. The findings revealed that perceived ease of use was strongly affected perceived usefulness. This study can help technologists to develop user-friendly and useful online platforms. Thus, useful online platforms enhance the users' perceived satisfaction and their continuous intentions to use online platforms, especially in MOOCs. Similarly, successful MOOCs platforms may help the users for their career growth, personal development, and willingness to learn new skills by using new technologies. Thus, technology ease of use and usefulness may enhance their loyalty toward MOOCs.

This research provides important insights and contributions to the SDT and TAM toward MOOCs. However, some limitations have been found in this research. It also suggests future research avenues to researchers to investigate in future research. First, we used convenience sampling for this research. While results generalization needs to use random sampling with a larger sample size in future research. Second, our study was limited to direct relationships of constructs. Future researchers may investigate the same model by checking the simple and serial mediation effects to contribute to theory and literature. Third, we collected data from three public universities in Wuhan, China. Future researchers may collect data from other cultures with a larger sample size to generalize the findings. Finally, the proposed model used the motivation and technology factors to predict the students perceived satisfaction and continuance use of MOOCs. Further research may consider more variables to check the effects of other theoretical variables and increase the intended users with various backgrounds (such as working professionals in government and private organizations) for more contributions and valuable insights.

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